Journal of Biological Engineering Research and Review, 2021; 8(2): 83-90
ISSN: 2349-3232 Online
Available online at www.biologicalengineering.in/Archive

Research Article

A Stacked Bi-directional Long Short Term Memory Framework for the Single and Multi-Step Ahead Hourly Time Series Forecasting of Reference Evapotranspiration

Sowmya M R[1], Santosh Kumar M B[1], Sooraj K Ambat[2]

[1] *Cochin University of Science and Technology, Kochi, Kerala, India,*

[2] *Naval Physical and Oceanographic Laboratory, Kochi, Kerala, India*

***Corresponding author. E-mail:** sowmyamr@cusat.ac.in **(Sowmya M R)**

ARTICLE INFO:

Article History:
Received: 22/06/2021
Revised: 18/10/2021
Accepted: 11/11/2021
Published: 31/12/2021

Keywords:
Bidirectional LSTM, Recursive feature elimination, Time series forecasting, Reference evapotranspiration,

Citation: Sowmya M R, Santosh Kumar M B, and Sooraj K Ambat. A Stacked Bi-directional Long Short Term Memory Framework for the Single and Multi-Step Ahead Hourly Time Series Forecasting of Reference Evapotranspiration. Journal of Biological Engineering Research and Review. 2021, 8(2): 83-90.

Abstract: Precision agriculture considers reference evapotranspiration (ETo) as a significant meteorological parameter for estimating crop water need and thus planning precision irrigation. This paper proposes a stacked bi-directional long short-term memory (BLSTM) framework for the hourly forecasting of ETo. The recursive feature elimination (RFE) process was employed to select the optimal feature lag for the model construction. Single and multi-step ahead ETo forecasting models with stacked BLSTM and LSTM architectures were developed using RFE suggested 24 feature lags as input and the prediction horizons of 1, 6, 12, and 24. The evaluation process verified the efficiency of stacked BLSTM models over stacked LSTM models in all prediction horizons. The study reported the best accuracy for the single-step ahead ETo forecasting model, BLSTM 24-1, with a mean absolute error (MAE) of 0.94 mm/hour, a root mean squared error (RMSE) of 1.7 mm/hour and a coefficient of determination (R2) of 0.91. Though the shorter horizon improves the forecasting accuracy, the negligible variations in the performance metrics observed in the multi-step ahead models, such as 1.31–1.11 mm/hour in MAE, 2.38–2.11 mm/hour in RMSE, and 0.83–0.86 in R2, emphasized the supremacy of stacked BLSTM architecture in ETo hourly forecasting, irrespective of the prediction horizon. Hence, in addition to the most reliable one-step ahead BLSTM model, this study also recommends the 24 hours ahead BLSTM model as a daily irrigation planning tool for agriculturists by aggregating its output time series.

INTRODUCTION

Agriculture, the world's most water-intensive activity [1], is currently looking for some innovative precision irrigation techniques that promote wise water usage and assist farmers in achieving higher levels of crop yield in a lesser amount of water. The precise estimate of the amount of water needed for a crop to grow serves as the basis of precision irrigation techniques [2], and it is closely related to the term evapotranspiration (ET) in the hydrologic cycle [3]. The combined processes of surface evaporation and plant transpiration define the evapotranspiration [2], and a variant of it, the reference evapotranspiration (ETo,) is a meteorological parameter for calculating the actual ET of different crops [4].

ETo can be directly measured with a lysimeter, but its complexity necessitates the development of various empirical equations to estimate ETo [5]. Among these, the Penman-Monteith equation (FPME) developed by the Food and Agriculture Organization of the United Nations is considered as the standard ETo estimation method [6]. The need for a large number of meteorological variables for its estimation, as well as their unavailability in many areas, paved the way for the use of artificial intelligence (AI) techniques in ETo modelling [7]. Several minimal input parameter-based ETo modelling studies have taken advantage of the ability of AI algorithm to portray the nonlinear relation between input parameters and ETo [8]–[10]. Moreover, the short-term or long-term forecasting of ETo will help agriculturists to plan irrigation and manage their water supplies more effectively [11]. However, majority of ETo modelling research has focused on the estimation of ETo using multiple input variables such as temperature, humidity, wind speed and solar radiation [5]. Univariate analysis and time series forecasting studies based on ETo, resulting in multiple steps ahead ETo time series values, are limited in the literature.

Related Work

The deep learning-based time series data analysis of ETo is emerging in the ET domain because of its competence to learn the ETo data pattern. ETo forecasting studies using time-lagged recurrent neural networks (TLRNN) [12], encoder-decoder long short-term memory (LSTM) [13], bidirectional LSTM (BLSTM) [14]- [16], hybrid and ensemble deep learning architectures [11], [17] demonstrated this. Proias et al. [12] made a one to three days ahead ETo forecast using TLRNN. According to the multi-step ahead daily ETo forecasting study report of Ferreira and Cunha [11], the Convolutional LSTM hybrid model performed well in local and regional scenarios. In another study [18], they tried to estimate daily ETo from various input parameters measured hourly and reported a fair result. Using a multivariate hybrid BLSTM model, Yin et al. [15] successfully forecasted a short-term, 1–7 day ahead ETo time series. Roy [16] investigated the potential of BLSTM in the one-step ahead forecasting of daily ETo time series. However, apart from these few studies, the analysis of deep learning architectures in ETo modelling, especially in time series forecasting, is very limited.

Previous ETo time series forecasting studies have produced results ranging from shorter forecast periods of one to seven days [19], [20] to longer forecast horizons of several months, spanning one to several steps forward [15], [21]– [25]. Most of them have used neural networks in their modelling. Manikumari et al. [26] employed boosted and bagged neural networks in the daily ETo time series forecasting up to 365 days and proved its success in comparison with artificial neural network (ANN) models. Nourani et al. [21] observed an accurate single and multi-step ahead ETo forecast using monthly time series inputs with ensemble models. Gocic and Amiri [22] investigated the effect of using the optimal input time lags for the prediction of monthly ETo using ANN. Certain studies have conducted multi-step ahead ETo forecasting with prediction horizons such as 1–30 days [27] and 16 days [28]. To the best of author's knowledge, no studies on hourly ETo time series forecasting to generate one-step or multi-step ahead ETo forecasts have been identified in the literature to date.

The ability of the LSTM and its derivatives to learn long-term input-output dependence [29] propelled them to the top among forecasting research. Additionally, the BLSTM architecture can retain both past and future time series in forecasting modelling, resulting in more accurate results [15]. Hence, we opted to experiment with stacked BLSTM architectures for the proposed investigation of hourly ETo forecasting.

An optimal input feature or lag of a time series forecasting model is a critical factor for determining its accuracy [22]. The recursive feature elimination (RFE) is a feature selection method that seeks an optimal time lag by recursively eliminating least important features of the model [30]. Some forecasting studies implemented it [30], [31], but ETo forecasting studies never attempted RFE for optimal feature selection. Summarizing the aforementioned points, the objectives of the proposed study are

- to design and implement stacked BLSTM architecture for the single and multi-step ahead time series forecasting of ETo on an hourly basis,
- to select the optimum feature lag for the proposed model by using RFE feature selection methodology, and
- to evaluate the efficiency of the proposed method in contrast to the stacked LSTM architecture.

METHODS AND MODELS

Data set and data preparation

The present study used the hourly ETo time series data estimated from the meteorological data such as temperature, humidity, net solar radiation, and wind speed. The hourly meteorological data from November 2015 to February 2021 was collected from the Advanced Centre for Atmospheric Radar Research (ACARR), Cochin University of Science and Technology in Kochi, Kerala, India. The ASCE-Penman Monteith equation (APME) was applied to 46324 data records to estimate hourly ETo. APME is a variant of FPME for estimating ETo on an hourly basis [18] and is given by (1).

$$ETo = \frac{0.408\,\Delta\,(R_n - G) + \gamma\left(\frac{37}{T_m + 273}\right)u_2(e_s - e_a)}{\Delta + \gamma(1 + C_h u_2)} \quad (1)$$

where ETo is the reference evapotranspiration (mm/hour), Δ is the slope of vapour pressure curve (kPa/0C), γ is the psychometric constant (k Pa0 C-1), R_n is the net solar radiation (MJm-2hour-1),), e_s is mean saturation vapour pressure(kPa), e_a is actual vapour pressure (kPa), G is the soil heat flux (MJm-2hour-1), T_m is the daily maximum temperature (0C), u_2 is the wind speed at 2m height (m/s), C_h is a constant with a value 0.24 during day time and 0.96 during night time.

To ensure faster learning and convergence, min-max normalization was applied to the input time series data for model training. Missing time series values were imputed using interpolation technique. Statistical properties of the processed data are listed in Table 1.

Table 1: Statistical description of the ETo time series data

Count	Max	Min	Mean	Standard deviation	Unit
46324	24.4	-2.0	2.4	4.9	Millimeter/ hour

RFE feature selection

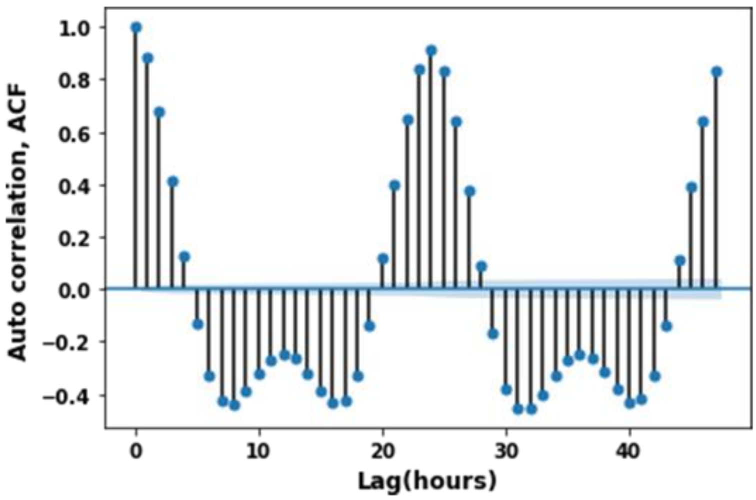
A well-designed feature selection process often improves the precision of a machine learning forecasting model. In the univariate forecasting approach, the observations in the previous time steps or lag values form the input features of the model. Because the lag determines the length of historical time series records, an optimal selection of it often results in a suitable input vector to the forecasting model, reducing computation time and increasing forecasting precision [22].

RFE is a wrapper methodology that trains the forecasting model with the original feature set of a certain time steps and ranks the lag features by significance [30]. The pruning process is then carried out on the lags with the lowest score. This process is repeated with a progressively smaller subset, which is reduced by the desired number of features [31].

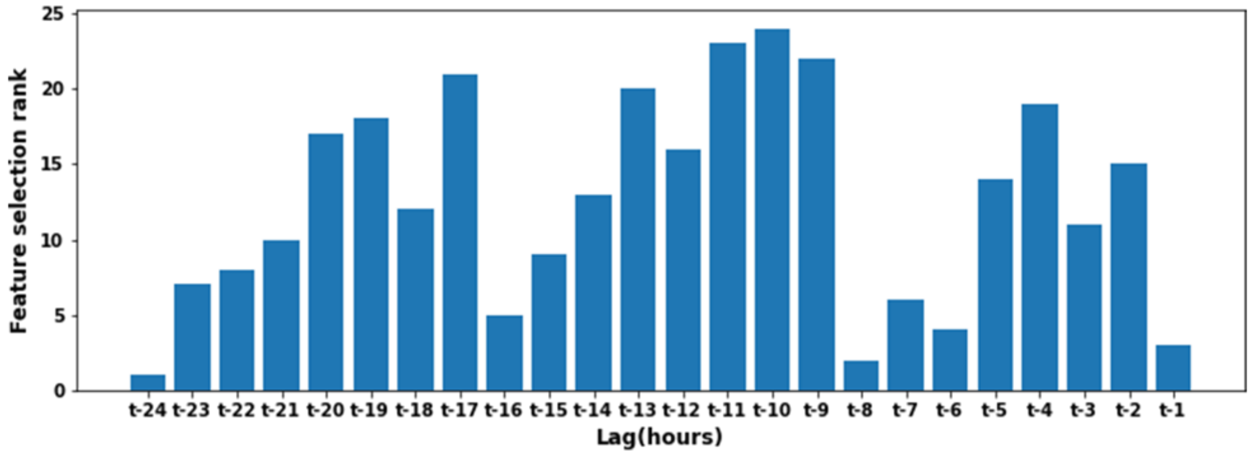
This study used RFE to perform experiments for optimum lag selection, by setting the original feature set with 1-to-24-time steps and the desired number of input features to 1. The best lag values obtained is 24, as seen in Fig 1. Fig 1(a) depicts the correlation of each lag observation, while Fig 1(b) depicts the feature selection rank (smaller is better) for each input feature.

Proposed Stacked BLSTM framework

BLSTM is a deep learning architecture consisting of two separate recurrent neural networks in charge of preserving past and future time series information. Unlike unidirectional LSTM, which only considers the previous history of observations, BLSTM processes time series observations in both forward and backward directions [14]. The forward and backward layers do not allow information to flow in between, but both direct the information to the output layer. The individual forecast of each BLSTM unit is aggregated to determine the final forecast. Because BLSTM is an extended version of LSTM, it inherits its ability to capture the long-term interactions among the time series data by avoiding the vanishing or exploding gradient issues [15]. The structure of BLSTM architecture is depicted in Fig 2.



(a) Correlogram



(b) Feature selection rank

Fig 1: Optimal feature lag selection using (a) correlogram and (b) RFE from the ETo time series dataset

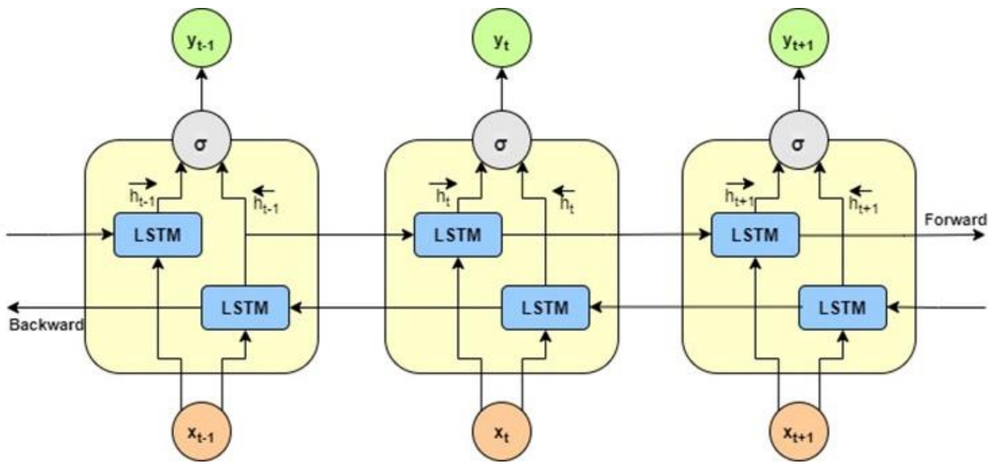


Fig 2: Structure of BLSTM model

The BLSTM calculates the final output y_t by aggregating the forward layer output, $\overrightarrow{h_t}$ and backward layer output, $\overleftarrow{h_t}$. x_{t-1}, x_t, and x_{t+1} are the input time lag values, and y_{t-1}, y_t, and y_{t+1} are the output time lag values. The information flow between the layers can be mathematically represented as (2), (3), and (4).

$$\overrightarrow{h_t} = f\left(w_1 x_t + w_2 \overrightarrow{h_{t-1}}\right) \quad (2)$$

$$\overleftarrow{h_t} = f\left(w_3 x_t + w_5 \overleftarrow{h_{t+1}}\right) \quad (3)$$

$$y_t = g\left(w_4 \overrightarrow{h_t} + w_6 \overleftarrow{h_t}\right) \quad (4)$$

where w_1 and w_3 are input to hidden layer (both forward and backward) weights, w_2 and w_5 are the weights between hidden layers, and w_4 and w_6 are hidden layer to output layer weights.

In this study, the characteristics of a BLSTM unit has been exploited to achieve an improved ETo forecast by stacking multiple units of it. The proposed stacked BLSTM framework for the hourly ETo forecasting for both single and multiple step ahead contains two stacked BLSTM layers, each one with 50 units along with a dropout layer with 0.2 dropout rate. During the model's training phase, the ReLu activation and Adam optimization algorithms were used. The best results were obtained for a batch size of 256, a learning rate of 0.001, and an epoch size of 200. All of these parameters were chosen using a trial-and-error strategy, and the results of such experiments are discussed in section IV.

ETo forecasting strategies for the proposed model implementation

The proposed research considers two strategies for ETo forecasting: one step ahead and multi-step ahead, both experimenting with optimal input time lag of 24 according to the findings described in section II. The prediction horizon for multi-step ahead ETo forecasting is randomly chosen as 6 hours, 12 hours, and 24 hours, while the prediction horizon for the single step forward is one. In addition to the proposed stacked BLSTM model, a unidirectional stacked LSTM model has also been designed and tested for performance evaluation. The entire time series data was split in a 70:30 ratio for model training and testing.

Both the stacked LSTM and BLSTM architectures were tested with one to three stacked layers with a search space of 10, 20, 30, 50, 70, and 100 units. To prevent overfitting problems, the dropout layers were used in the architecture with an experimented dropout rate of 0.1, 0.2, and 0.3. The batch sizes tested were 128, 256, and 516, and an overall epoch of 300 with early stopping was also used. The built models are labelled according to the architecture used, the number of input time lags, and the prediction horizon length. The values of hyper parameters and layer configuration of the proposed and evaluation models are listed in Table 2.

Performance evaluation criteria

The proposed stacked BLSTM models for both one and multi-step forward ETo forecasting were compared to the stacked LSTM models using the error indicators such as mean absolute error (MAE), root mean square error (RMSE), and the coefficient of determination (R^2) [11]. The proficiency of the constructed models is characterized by a lower value of MAE and RMSE and a higher value of R^2. These statistical performance indicators are represented in (5), (6), and (7).

$$MAE = \frac{1}{n}\sum\left|ET_p - ET_a\right| \quad (5)$$

$$RMSE = \sqrt{\frac{1}{n}\sum\left(ET_p - ET_a\right)^2} \quad (6)$$

$$R^2 = \left(\frac{\sum\left(ET_p - \overline{ET_p}\right)\left(ET_a - \overline{ET_a}\right)}{\sqrt{\sum\left(ET_p - \overline{ET_p}\right)^2 \sum\left(ET_a - \overline{ET_a}\right)^2}}\right)^2 \quad (7)$$

where n is the number of data records, ET_p is the predicted ETo values, ET_a is the actual ETo values, $\overline{ET_p}$ is the mean of predicted ETo values, $\overline{ET_a}$ is the mean of actual ETo values.

RESULTS AND DISCUSSIONS

This section analyses the performance of the proposed stacked BLSTM ETo forecasting model architecture to the stacked LSTM architecture in both single step ahead and multi-step ahead forecasting scenarios. For the design of the

Table 2: Layer configuration and hyper parameter settings of the built models

Model architecture	Horizon length	Model name	Hyper parameter	Value
Stacked BLSTM	1 6 12 24	BLSTM 24-1 BLSTM 24-6 BLSTM 24-12 BLSTM 24-24	Stacked layers	2
			Units	50
			Dropout	0.2
			Batch size	256
			Epoch	300
Stacked LSTM	1 6 12 24	LSTM 24-1 LSTM 24-6 LSTM 24-12 LSTM 24-24	Stacked layers	2
			Units	(100, 50)
			Dropout	0.2
			Batch size	256
			Epoch	300

Table 3: Performance metrics of ETo forecasting models during the testing period

Forecast strategy	Horizon	BLSTM			LSTM		
		MAE	RMSE	R^2	MAE	RMSE	R^2
One step	1	0.94	1.7	0.91	0.99	1.8	0.89
Multi step	6	1.11	2.11	0.86	1.33	2.26	0.84
	12	1.3	2.31	0.84	1.39	2.44	0.81
	24	1.31	2.38	0.83	1.4	2.5	0.8

models, the ETo time series data was pre-processed with time steps of 24 observations looking backward and 1-, 6-, 12-, and 24-time steps looking forward. The assessment metrics derived from evaluating the models with test data are listed in Table 3 and illustrated graphically in Fig 3.

Performance evaluation of the proposed model in single step ahead forecasting

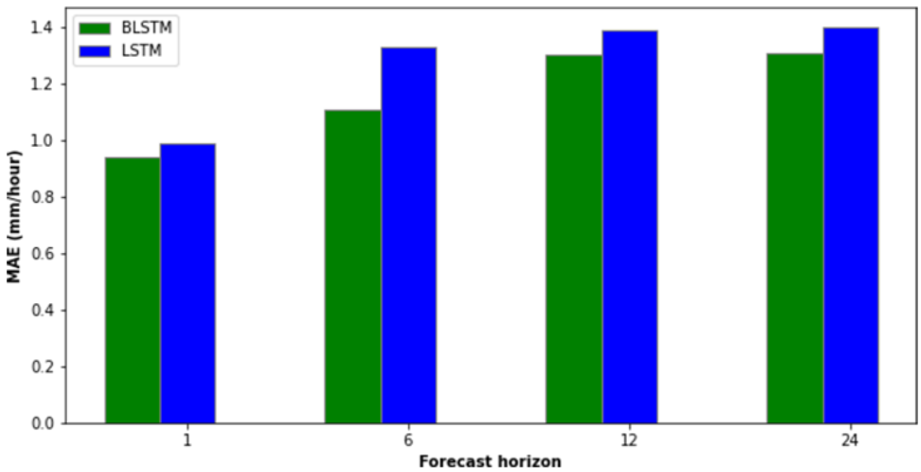
All the performance indicators in Table 3 denote the superiority of BLSTM 24-1 over LSTM 24-1. The percentage decrease of 5 in MAE, 5.6 in RMSE, and a percentage increase of 2.3 in R2 of stacked BSLTM compared to LSTM 24-1, demonstrate its effectiveness in hourly and single step ahead ETo forecasting.

Performance evaluation of the proposed model in multi-step ahead forecasting

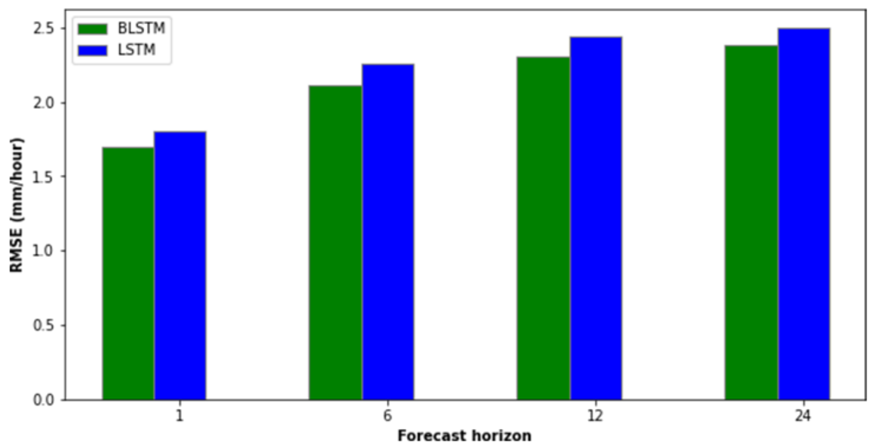
All the multi-step ahead forecasting models based on the stacked BLSTM architecture (BLSTM 24-6, BLSTM 24-12, and BLSTM 24-24) outperformed the stacked LSTM forecasting models (LSTM 24-6, LSTM 24-12, and LSTM 24-24). In comparison to LSTM 24-6, BLSTM 24-6 showed a percentage decrease of 16.5 in MAE, 6.6 in RMSE, and a percentage rise of 2.4 in R2. Both BLSTM 24-12 and BLSTM 24-24 exhibited a similar percentage of decrease of 6.4 in MAE, and 3.7 percentage of increase in R2, but a different percentage decrease of 5.3 and 4.8 in RMSE compared to LSTM 24-12, and LSTM 24-24. These findings demonstrate the efficacy of stacked BLSTM architecture in multi-step ahead hourly ETo forecasting.

Result analysis

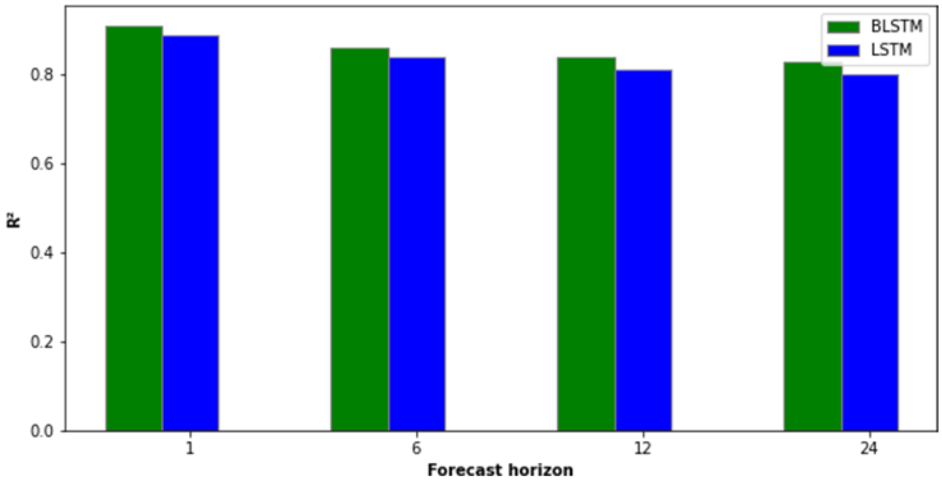
Regardless of the forecasting strategies, the stacked BLSTM architectures proved its ability in the hourly forecasting of ETo in this research. Fig 4, which shows the comparison of a sample forecasted and actual ETo time series, substantiates this. For all prediction horizons, BLSTM forecasted ETo values have a close correlation with actual ETo values in comparison with the LSTM forecasted ETo. The plot also highlights that the accuracy of the prediction decreases with the increase in the forecasting horizon length.



(a) MAE

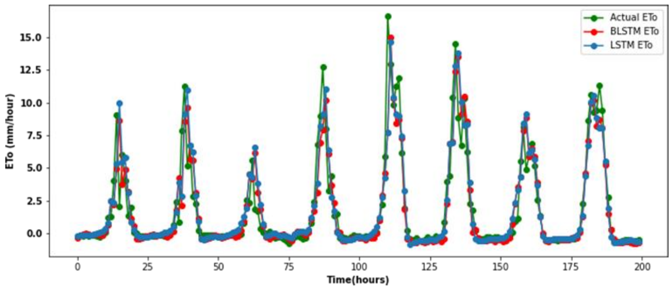


(b) RMSE

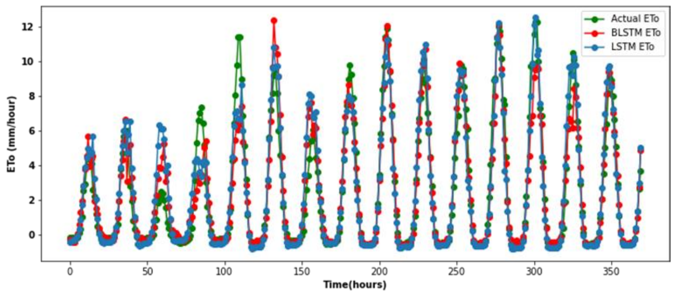


(c) R^2

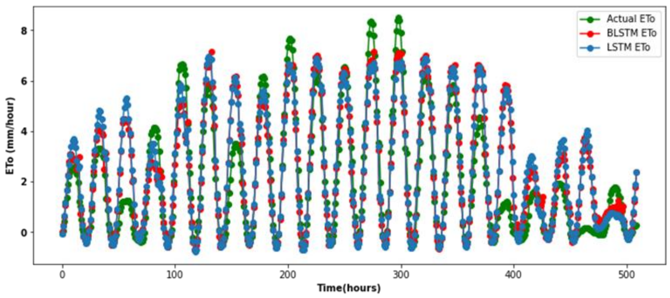
Fig 3: Comparison of the performance evaluation metrics for stacked BLSTM and LSTM models for single and multi-step ahead forecasting



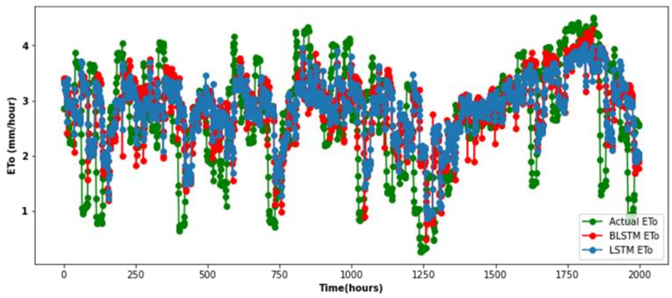
(a) One step forward



(b) 6 steps forward



(c) 12 steps forward



(d) 24 steps forward

Fig 4: Comparison of predicted and actual hourly ETo time-series values using stacked BLSTM and LSTM models for single and multi-step ahead forecasting

From the Table 3, the lowest values of MAE (0.94 mm/hour) and RMSE (1.7 mm/hour) as well as the highest value of R2 (0.91) were observed with the horizon length of 1, and it gradually changed to 1.31 mm/hour of MAE, 2.38 mm/hour of RMSE and 0.83 of R2 corresponding to the metric values of BLSTM 24-24. Although there exists a significant difference (15–28 % decrease in MAE, 19–28 % decrease in RMSE, 6–10 % increase in R2) between the single and multi-step forward forecasting performance, there is only a marginal performance variation among the multi-step ahead models.

Previously published ETo forecasting studies employed FPME recommended daily ETo values as input series to generate single and multi-step ahead daily and monthly ETo time series. The deep learning research conducted by Ferreira and Cunha [18] experimented with various hourly measured input data combinations to estimate daily ETo both directly and indirectly (by adding the predicted hourly ETo for 24 hours). It proved the efficacy of hourly input data in the accurate estimation of daily ETo. Hence, in addition to recommending a stacked BLSTM-based, single-step-ahead ETo forecast model, the present study reached another conclusion by relating the findings of the research of Ferreira and Cunha [18]. That is, BLSTM 24-24 is the most significant of the developed multi-step-ahead hourly ETo forecasting models because it can forecast the next 24 hours of ETo values, leading to the daily ETo forecast by summing its output forecast.

CONCLUSION

ETo hourly forecasting is a novel field of research in the ET domain. This paper investigates the capability of the stacked BLSTM deep learning framework in the hourly forecasting of ETo, incorporating single and multi-step ahead forecasting horizons. An optimal lag of ETo time series for the reliable forecasting was identified by applying the RFE feature selection method. Using an optimal lag of 24 observations from the ACARR time series data set, four models with different forecast horizons of 1, 6, 12, and 24 were designed, each using both stacked BLSTM and LSTM. When the efficiency of the designed architectures was evaluated using various statistical assessment criteria, stacked BLSTM surpassed stacked LSTM in both single and multi-step ahead ETo forecasting. Of the developed models, the single step ahead ETo forecasting model showed the best forecasting accuracy. In addition to the observation that a shorter forecasting horizon improves forecasting precision, multi-step ahead models have provided comparable accuracy to single-step models, with no substantial difference in forecasting efficiency between them. Furthermore, by aggregating its output forecast of 24 ETo values, the BLSTM 24-24 model can be used as a daily ETo calculator, assisting agriculturists in precisely planning irrigation.

ACKNOWLEDGEMENT

The authors would like to convey their deep gratitude to the Advanced Centre for Atmospheric Radar Research (ACARR), Cochin University of Science and Technology in Kochi, Kerala, India, for supplying meteorological data for this work.

CONFLICT OF INTEREST

Authors declare that no competing interests exist.

REFERENCES

1. O. Mohammadrezapour, I. Yoosefdoost, and M. Ebrahimi, "Cuckoo optimization algorithm in optimal water allocation and crop planning under various weather conditions (case study: Qazvin plain, Iran)," Neural Comput. Appl., vol. 31, no. 6, pp. 1879–1892, 2019, doi: 10.1007/s00521-017-3160-z.
2. R. G. Allen, L. S. Pereira, D. Raes, and M. Smith, "Crop evapo transpiration-Guidelines for computing crop water requirements-FAO Irrigation and drainage paper 56," FAO, United Nations, Rome, vol. 300, no. 9, p. D05109, 1998.
3. L. Xu et al., "Spatiotemporal variation and driving forces of reference evapotranspiration in Jing River Basin, northwest China," Hydrol. Process., vol. 29, no. 23, pp. 4846–4862, 2015, doi: 10.1002/hyp.10541.
4. J. Fan et al., "Evaluation of SVM, ELM and four tree-based ensemble models for predicting daily reference evapotranspiration using limited meteorological data in different climates of China," Agric. For. Meteorol., vol. 263, no. February, pp. 225–241,2018, doi: 10.1016/j.agrformet.2018.08.019.
5. M. Y. Chia, Y. F. Huang, C. H. Koo, and K. F. Fung, "Recent advances in evapotranspiration estimation using artificial intelligence approaches with a focus on hybridization techniques—A review," Agronomy, vol. 10, no. 1, 2020, doi: 10.3390/agronomy10010101.
6. K. Xiang, Y. Li, R. Horton, and H. Feng, "Similarity and difference of potential evapotranspiration and reference crop evapotranspiration – a review," Agric. Water Manag., vol. 232, p. 106043, Apr. 2020, doi: 10.1016/J.AGWAT.2020.106043.
7. T. Wu, W. Zhang, X. Jiao, W. Guo, and Y. Alhaj Hamoud, "Evaluation of stacking and blending ensemble learning methods for estimating daily reference evapotranspiration," Comput. Electron. Agric., vol. 184, no. March 2020, p. 106039, 2021, doi: 10.1016/j.compag.2021.106039.
8. M. M. Reis, A. J. da Silva, J. Zullo Junior, L. D. Tuffi Santos, A. M. Azevedo, and É. M. G. Lopes, "Empirical and learning machine approaches to estimating reference evapotranspiration based on temperature data," Comput. Electron. Agric., vol. 165, p. 104937, Oct. 2019, doi: 10.1016/J.COMPAG.2019.104937.
9. M. Y. Chia, Y. F. Huang, and C. H. Koo, "Support vector machine enhanced empirical reference evapotranspiration estimation with limited meteorological parameters," Comput. Electron. Agric., vol. 175, no. April, 2020, doi: 10.1016/j.compag.2020.105577.
10. M. R. Sowmya, M. B. S. Kumar, and S. K. Ambat, "Comparison of deep neural networks for reference evapotranspiration prediction using minimal meteorological data," in 2020 Advanced Computing and Communication Technologies for High Performance Applications (ACCTHPA), 2020, pp. 27–33, doi:10.1109/ACCTHPA49271.2020.9213201.
11. L. B. Ferreira and F. F. da Cunha, "Multi-step ahead forecasting of daily reference evapotranspiration using deep learning," Comput. Electron. Agric., vol. 178, p. 105728, Nov. 2020, doi: 10.1016/J.COMPAG.2020.105728.
12. G. Proias, I. Gravalos, E. Papageorgiou, K. Poczęta, and M. Sakellariou-Makrantonaki, "Forecasting reference evapotranspiration using time lagged recurrent neural network," WSEAS Trans. Environ. Dev., vol. 16, no. October, pp. 699–707, 2020, doi: 10.37394/232015.2020.16.72.
13. K. Alibabaei, P. D. Gaspar, and T. M. Lima, "Modeling evapotranspiration using Encoder-Decoder Model," 2020 Int. Conf. Decis. Aid Sci. Appl. DASA 2020, pp. 132–136, 2020, doi: 10.1109/DASA51403.2020.9317100.
14. H. Afzaal, A. A. Farooque, F. Abbas, B. Acharya, and T. Esau, "Computation of evapotranspiration with artificial intelligence for precision water resource management," Appl. Sci., vol. 10, no. 5, 2020, doi: 10.3390/app10051621.
15. J. Yin, Z. Deng, A. V. M. Ines, J. Wu, and E. Rasu, "Forecast of short-term daily reference evapotranspiration under limited meteorological variables using a hybrid bi-directional long short-term memory model (Bi-LSTM)," Agric. Water Manag., vol. 242, no. February, p. 106386, 2020, doi: 10.1016/j.agwat.2020.106386.
16. D. K. Roy, "Long Short-Term Memory Networks to Predict One-Step Ahead Reference Evapotranspiration in a Subtropical Climatic Zone," Environ. Process., vol. 8, no. 2, pp. 911–941, 2021, doi: 10.1007/s40710-021-00512-4.
17. P. de Oliveira e Lucas, M. A. Alves, P. C. de Lima e Silva, and F. G. Guimarães, "Reference evapotranspiration time series forecasting with ensemble of convolutional neural networks," Comput. Electron. Agric., vol. 177, no. July, p. 105700, 2020, doi: 10.1016/j.compag.2020.105700.
18. L. B. Ferreira and F. F. da Cunha, "New approach to estimate daily reference evapotranspiration based on hourly temperature and relative humidity using machine learning and deep learning," Agric. Water Manag., vol. 234, no. February, p. 106113, 2020, doi:

10.1016/j.agwat.2020.106113.
19. G. Landeras, A. Ortiz-Barredo, and J. J. López, “Forecasting weekly evapotranspiration with ARIMA and artificial neural network models,” J. Irrig. Drain. Eng., vol. 135, no. 3, pp. 323–334, 2009, doi: 10.1061/(ASCE)IR.1943-4774.0000008.
20. A. Afifi, “Forecasting Reference Evapotranspiration Using Non-Linear Autoregressive Artificial Neural Network.” University of Hawai’i at Manoa, 2020.
21. V. Nourani, G. Elkiran, and J. Abdullahi, “Multi-step ahead modeling of reference evapotranspiration using a multi-model approach,” J. Hydrol., vol. 581, p.124434,2020, doi: 10.1016/j.jhydrol.2019.124434.
22. M. Gocić and M. Arab Amiri, “Reference Evapotranspiration Prediction Using Neural Networks and Optimum Time Lags,” Water Resour. Manag., vol. 35, no. 6, pp. 1913–1926, 2021, doi: 10.1007/s11269-021-02820-8.
23. X. Lu, J. Fan, L. Wu, and J. Dong, “Forecasting multi-step ahead monthly reference evapotranspiration using hybrid extreme gradient boosting with grey wolf optimization algorithm,” Comput. Model. Eng. Sci., vol. 125, no. 2, pp. 699–723, 2020, doi: 10.32604/cmes.2020.011004.
24. A. El-Shafie, H. M. Alsulami, H. Jahanbani, and A. Najah, “Multi-lead ahead prediction model of reference evapotranspiration utilizing ANN with ensemble procedure,” Stoch. Environ. Res. Risk Assess., vol. 27, no. 6, pp. 1423–1440, 2013, doi: 10.1007/s00477-012-0678-6.
25. H. Jahanbani and A. H. El-Shafie, “Application of artificial neural network in estimating monthly time series reference evapotranspiration with minimum and maximum temperatures,” Paddy Water Environ., vol. 9, no. 2, pp. 207–220, 2011, doi: 10.1007/s10333-010-0219-1.
26. N. Manikumari, A. Murugappan, and G. Vinodhini, “Time Series Forecasting of Daily Reference Evapotranspiration by Neural Network Ensemble Learning for Irrigation System,” IOP Conf. Ser. Earth Environ. Sci., vol. 80, no. 1, 2017, doi: 10.1088/1755-1315/80/1/012069.
27. M. Karbasi, “Forecasting of multi-step ahead reference evapotranspiration using wavelet-Gaussian process regression model,” Water Resour. Manag., vol. 32, no. 3, pp. 1035–1052, 2018, doi: 10.1007/s11269-017-1853-9.
28. R. Bachour, I. Maslova, A. M. Ticlavilca, W. R. Walker, and M. McKee, “Wavelet-multivariate relevance vector machine hybrid model for forecasting daily evapotranspiration,” Stoch. Environ. Res. risk Assess., vol. 30, no. 1, pp. 103–117, 2016, doi: 10.1007/s00477-015-1039-z.
29. Z. Han, J. Zhao, H. Leung, K. F. Ma, and W. Wang, “A Review of Deep Learning Models for Time Series Prediction,” IEEE Sens. J., vol. 1748, no. 2017, pp. 1–1, 2019, doi: 10.1109/jsen.2019.2923982.
30. J. Cruz, W. Mamani, C. Romero, and F. Pineda, “Selection of Characteristics by Hybrid Method: RFE, Ridge, Lasso, and Bayesian for the Power Forecast for a Photovoltaic System,” SN Comput. Sci., vol. 2, no. 3, pp. 1–14, 2021.
31. C. Feng, M. Cui, B.-M. Hodge, and J. Zhang, “A data-driven multi-model methodology with deep feature selection for short-term wind forecasting,” Appl. Energy, vol. 190, pp. 1245–1257, 2017.

About Authors

Sowmya M R, Research Scholar, Department of Computer Applications, Cochin University of Science and Technology, Kochi, Kerala, India.

Dr. Santosh Kumar M B, Associate Professor, Division of IT, School of Engineering, Cochin University of Science and Technology, Kochi, Kerala, India.

Dr. Sooraj K Ambat, Scientist - E, Defence Research and Development Organization (DRDO), Naval Physical and Oceanographic Laboratory (NPOL), Kochi, Kerala, India.